Decoding finger movements from ECoG signals using Empirical Mode Decomposition

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Abstract

ECoG promises exact localization of brain sources by providing high spatial resolution and good signal quality, thus making it the premier choice for future BCI applications. Unfortunately decoding these signals is not as straightforward as one would expect. In this work we applied a time-frequency analysis based on Empirical Mode decomposition (EMD) and Adaptive Filtering (AF) to decode and estimate the finger movement using 10 minutes-long, multi-channel ECoG signals. The dataset was recorded from three epileptic patients at Harborview Hospital in Seattle, Washington for Brain Computer Interface (BCI) Competition IV. Our proposed method showed the average correlation of 0.55 between real and predicted movement across the subjects and across fingers.

1 Introduction

Almost four decades ago, the first experimental endeavor on designing a BMI was accomplished by implementing the electrode on the motor cortex of monkeys by Fetz at al. [1] and training the brain to be able to control the external limb. Later on, similar research was done on rats by Nicolelis et. al [2] to teach rats to gain a sip of water by thinking about pushing a lever. This group introduced a closed-loop BMI recently for the first time, where the macaques were able to steer a robotic hand to grasp an object and simultaneously get tactile feedback [5].

The idea of linking the human brain to a machine and transforming the pure thinking power into mechanical or virtual actions attracted the attention of several research groups worldwide afterwards [3, 6, 8]. The authors in [6] have successfully demonstrated a brain computer interface that uses an electrode implanted into the motor cortex of the brain. In [7] authors describe the early stage development and initial human application of neural interface systems (NISs) for paralyzed humans based on an intra-cortical microelectrode sensor that derives control signals from the motor cortex.

Pioneered in the early 1950s by Penfield and Jasper, Electrocorticography (ECoG) or intracranial EEG (iEEG) systems use electrodes placed on the exposed surface of the brain directly under the skull to gather rhythmic neural activity created by a large group of neurons in the cerebral cortex [3]. The cortical potentials recorded by ECoG leads to higher spatial resolution, broader band width, higher signal to noise ratio and less sensitivity to motional artifacts compared to recordings over the scalp [4]. This fascinating technology is usually used to identify epileptogenic zones [9] but in the future these signals could be targeted as the input to a Brain Machine Interface (BMI) or Brain Computer Interface (BCI). Achieving higher reliability and accuracy is the agenda for designing and developing the new generation of BMIs. Signals recorded within cortex could be better candidates to encode more information and might support BMI systems that require less training than EEG-based systems [4]. This could be immediately used to augment control abilities by steering the movement of a prosthetic hand and its fingers.

For the fourth round of the BCI Competition, new challenging problems were introduced which are highly relevant for practical BCI. Dataset 4 was recorded with exactly the paradigm found in [6] in mind. Three epileptic patients scheduled to undergo surgery at Harborview Hospital in Seattle, Washington, were asked to move their fingers in a predefined way, while ECoG signals were recorded with Platinum grid electrodes placed on the motor area of the according hand. The dataset was originally published to evaluate the discrimination requirements for fine grained spatial resolution in ECoG. The aim of this paradigm is to predict the flexion of individual fingers from signals recorded from the surface of the brain (ECoG) just under the skull. The winner applied amplitude modulation
from band-specific ECoG and pair-wise feature selection in combination with linear regression with the performance of 0.46 [11]. The performance measure is defined by the correlation coefficient $r$ between the actual and the predicted finger flexions, averaged across all subjects and fingers (except for finger 4). Switching linear models controlled by a hidden state was proposed in [13] to decode finger flexion on the same database.

In this work we investigate a time-frequency analysis approach based on Empirical Mode decomposition (EMD) and Adaptive Filtering (AF) to decode and estimate finger movements using multi-channel ECoG signals. The goal is to demonstrate that ECoG can be used to continuously track which finger is currently being moved. Our result shows higher correlation coefficient compared to previously published results [11, 13].

2 Experimental Setup

Signals from the electrode grid were amplified and digitized using Synamps2 amplifiers (Neuroscan, El Paso, TX). The general-purpose BCI system BCI2000 provided visual stimuli to the patient, acquired brain signals from the Synamps2 system, and also recorded the flexion of individual fingers (on the hand contralateral to the implanted grid) using a data glove (Fifth Dimension Technologies, Irvine, CA) [6]. BCI2000 stored the brain signals, the timing of stimulus presentation, and the flexion of each of the fingers in a data file. Data files were converted to MATLAB format for this competition. The subjects were cued to move a particular finger by displaying the corresponding word (e.g., "thumb") on a computer monitor placed at the bedside [6]. Each cue lasted two seconds and was followed by a two-second rest period with a blank screen. During each cue, the subjects typically moved the requested finger 3-5 times. This number varied across subjects and fingers. There were 30 movement stimulus cues for each finger (i.e., a total of 150 cue presentations and about 90-150 flexions of each finger); stimulus cues were interleaved randomly. This experiment took 10 minutes for each subject [6]. The whole data set with recordings from all patients and all of their implanted electrodes is available under [16].

2.1 ECoG BCIs for Prosthetic Hand Control

Each patient had subdural electrode arrays (Ad-Tech, Racine, WI) implanted. Each array contained 48-64 platinum electrodes that were configured in 8x6 or 8x8 arrangements. The electrodes had a diameter of 4 mm (2.3mm exposed), 1 cm inter-electrode distance, and were embedded in silastic.

Electrocorticographic (ECoG) signals (i.e., 62, 48, and 64 channels from subjects 1, 2, and 3, respectively) were acquired with respect to a scalp reference and ground (Figure 1), band pass filtered between 0.15 to 200 Hz, and sampled at 1000 Hz.

Figure 1 ECoG BCI in Humans. (a) An 8x8-electrode array was placed under the dura of a patient. The electrodes are 2mm in diameter and separated from each other by 1 cm. Ant: anterior. (b) X-ray image of the skull showing the location of the electrode array [14].

Figure 2 demonstrates the finger movements’ measurements using a Dataglove. Outputs of five finger sensors were recorded simultaneously while recording from the implemented array of about 64 electrodes on each subject’s cortex.

Figure 2 Individual finger flexion recorded from subject 1 in the first 10s of the experiment.

3 Materials and Methods

Empirical Mode Decomposition is a method to decompose a given function into a set of different intrinsic oscillation modes also known as Intrinsic Mode Function (IMF) [12]. Each IMF enjoys good Hilbert transform. We extracted the set of features applying the Hilbert transform on each IMF and calculated the amplitude and phase of each to feed into an adaptive filter with desired signal captured from individual finger flexion. The first 2/3 recorded data sampled at 1 kHz was used to train
the filter; the rest of data was used to predict the proper finger position.

3.1 Empirical Mode Decomposition

Empirical Mode decomposition introduced by Huang [12] is a heuristic approach for analyzing nonlinear non-stationary data. Under this adaptive and efficient decomposition each time series can be decomposed into a finite number of different intrinsic oscillation modes called Intrinsic Mode Functions (IMFs) which are in most cases physically meaningful representations of data. The procedure contains a sifting algorithm followed by subtracting the extracted IMF from the signal. The final results can be summarized as equation (1). The complete sifting procedure is illustrated in [12]

\[ x(t) = \sum_{j=1}^{n} c_j + r_n \]  

(1)

3.1.1 Hilbert Transform

IMFs are designed to behave well under Hilbert transform [12], which can be calculated as:

\[ g(y) = H(f(x)) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{f(x)dx}{x-y} \]  

(2)

The result is actually a 90 degree phase shifted version of the input data. This function can also calculate the imaginary part of an analytic signal corresponding to the input data. An analytic signal is a signal that has no negative frequency component.

\[ z(t) = f(x) + jH(f(x)) \]  

(3)

\[ z(t) = a(t) \exp(j\theta(t)) \]  

(4)

Consequently the instantaneous frequency can be calculated using \( d\theta(t)/dt \).

3.1.2 Feature Extraction

In order to gain insights into the relation of the ECoG and the finger flexion and investigate the logical decoding algorithm we need to extract the most proper and informative features from the input signal. We chose to use a subset of about 10 electrodes which were the most varying in amplitude over the time. The goal is predicting each finger flexion from this subset of ECoG signals.

We extracted the first 20 IMFs from the each selected channel in the train data, but finally a subset of 5 IMFs was selected as the input to the next stage. We examined different IMF in the test dataset and finally we chose IMFs which their instantaneous frequency lies closest to the range of 10Hz, 30Hz, 75Hz, 100Hz and 130Hz. The best results were achieved when these bands were selected. These signals provide the input to an entropy based adaptive filter for each finger where the reference signal is the corresponding recorded signal while moving that finger. Figure 3 shows a sample of the average power over the electrode array after 1s, 2s, 3s, and 4s of recording.

![Figure 3](image-url)

**Figure 3** Average power over the electrode array after 1s, 2s, 3s, and 4s of recording

3.2 Adaptive Filter

Adaptive filtering (AF) theory uses mean square error (MSE) criteria to adapt the filter weights such that it converges to an optimum solution in the data space. It can be argued that MSE is not always the best possible criterion to use in adaptation. In fact, the minimization of MSE is just taking the second-order moment of the error distribution into consideration, which is optimal only for Gaussian distributed errors. In cases where the error distribution is not Gaussian, it makes sense to study alternate cost functions for adaptation [15]. Here we take a different approach using information-theoretical concepts, and propose the error entropy criterion (EEC). In EEC the goal of adaptation should be to remove as much uncertainty as possible from the error signal [15]. The error signal is the difference between the outputs and the desired signal. In an AF the desired response can be considered as being created by an unknown transformation of the input vector.

![Figure 4](image-url)

**Figure 4** Block diagram of the proposed method

After the filter weights converged within a satisfactory time, we used the same values to anticipate the individual finger movements from the
input data. For this purpose we used 5 separate but parallel structures of AF each corresponding to one particular finger.

4 Results

One memorable result of the whole contest is to prove the ability of cortical signals to predict accurate movements. This is most encouraging on the path to develop a BCI system by fine controlling e.g. an artificial hand for paralyzed people.

In order to evaluate the performances of our methods we calculated the same correlation factor between measured and predicted finger flexions, as proposed by competition committee [16]. The general evaluation of performance is measured by calculating the correlation coefficient \( r \) between the actual and the predicted finger flexions, averaged across subjects and across fingers. However the highest correlation was calculated for the first finger of the third subject with 0.68. It is depicted in Figure 5. The fourth finger was excluded from the evaluation, because its movements were highly physically correlated with those of the other finger. The final predictions values are reported in Table 1.

Table 1 correlation coefficient \( r \) between the actual and the predicted finger flexions, averaged across subjects and across fingers

<table>
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<tr>
<th>Finger</th>
<th>Subject1</th>
<th>Subject2</th>
<th>Subject3</th>
<th>Ave</th>
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<tr>
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</table>

5 Conclusion

A precise prediction of movement is a challenging topic in Brain Computer Interfacing. It can provide a control signal for a prosthetic or a robotic hand with better quality of signal and consequently higher accuracy and localization in control. The price for this is the partial invasiveness of the method. In this work, a joint time-frequency-space approach based on EMD was used to predict the finger movement for the 4min test data. Features have been selected regarding the instantaneous frequency of IMFs which were fed to an entropy-based adaptive filter. Here the desired input to decode finger movement using IMFs with specific spontaneous frequency was extracted from multi-channel ECoG signal. The result show promising accuracy compared to similar EEG-based BCIs On the quest to control complex bionic prostheses with high degrees of freedom.

6 References